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Adaptive Color Display via Perceptually-driven Factored Spectral Projection

EE368 Final Project (Paper submitted to SIGGRAPH Asia 2015)

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Problem

Core display characteristics are constantly being improved, fore-most resolution, dynamic range, and color reproduction. However, it remains largely unclear how to extend the color gamut of a display without either sacrificing light throughput, color fidelity or making other tradeoffs. In this project, We build a flexible gamut projector and develop a perceptually-driven optimization framework (PNMF) that robustly factors a wide color gamut target image into a set of time-multiplexed primaries and corresponding pixel values. We demonstrate that PNMF has many benefits over fixed gamut selection and show that our algorithm for joint primary selection and gamut mapping performs better than existing methods.

Previous Work

In the last few years a trend towards adaptive color processing is observable. The most well-known techniques have been proposed recently is to use non-negative matrix factorization(NMF) to optimize this problem in CIE XYZ space[Pauca et al. 2006; Ben-Chorin and Eliav 2007]. In addition, Rodriguez et al. [2012] recently proposed to determine the optimal gamut that maximizes total gamut volume in CIE Luv space. Here, we argue that there is no single optimal gamut in general, and that the best gamut depends on the content to be displayed. We also argue that image optimized in CIE XYZ space do not provide perceptually best approximation.

Image Formation

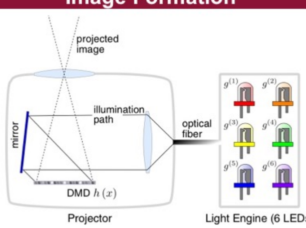

FIGURE 1: Proposed Setup

The proposed setup is illustrated in Fig. 1 and comprises a standard digital micromirror device (DMD) that rapidly changes pixel values. Instead of sequentially cycling through traditional fixed three primaries, our light engine allows each color primary to be dynamically chosen as a weighted combination of 6 high-power light emitting diodes(LEDs):

$$\mathbf{I}^{(xyz)} = \mathbf{P}^{(xyz)}\mathbf{\Psi}\mathbf{G}\mathbf{H}^T = \mathbf{PGH}^T$$

Above equation defines the captured image in CIE XYZ color space, where matrix $\mathbf{P}^{(xyz)}$ contains the discretized versions of spectral sensitivity of the three cones, matrix $\mathbf{\Psi} \in \mathbb{R}^{L\times M}$ encodes the discrete spectral basis functions in its columns, matrix $\mathbf{G} \in \mathbb{R}^{M\times K}$ is the temporally-varying weights of the LEDs, and matrix $\mathbf{H} \in \mathbb{R}^{N\times K}$ represents the pixels values of a total of N pixels.

PNMF vs. NMF

Given a set of primaries along with an image that potentially exceeds the gamut spanned by the primaries, what is the closest approximation to the target image we can display?

NMF:

Compute the least-squares solution in CIE XYZ space by solving the following objective function:

$$\underset{\{\mathbf{H}\}}{\arg\min} \left\|\beta\mathbf{I}^{(xyz)} - \mathbf{PGH}^T\right\|_2^2 \quad \text{subject to} \quad 0 \le \mathbf{H}_{jk} \le 1,\ \forall j,k$$

The scalar $\beta \in [0, 1]$ can be useful for digitally trading image brightness for color accuracy. Non-negative constraints enforce physical constraints of feasible pixel values. This problem can be solved by multiplicative update rule proposed by Lee and Seung[1999]

•*Gamut Mapping*

$$\mathbf{H} \leftarrow \mathbf{H} \circ \frac{(\mathbf{PG})^T \beta\mathbf{I}^{(xyz)}}{(\mathbf{PG})^T(\mathbf{PGH}^T)+\epsilon}$$

Above equation ensures with a purely positive guess of H, it will remain positive through iterations.

•*Primary Selection*

$$\mathbf{G} \leftarrow \mathbf{G} \circ \frac{\mathbf{P}^T \beta\mathbf{I}^{(xyz)}\mathbf{H}}{\mathbf{P}^T(\mathbf{PGH}^T)\mathbf{H}^T+\epsilon}$$

Applying H and G update iteratively until convergence yields the final approximation

Drawback: Euclidean distances in CIE XYZ coordinates is not perceptually uniform. Low ℓ_2 error may not actually represent a good perceptual approximation.

PNMF:

Compute the least-squares solution in CIE Lab space, in which the color difference is at least locally linear,

$$\underset{\{\mathbf{G},\mathbf{H}\}}{\text{minimize}} \left\|\beta\mathbf{I}^{(lab)} - \varphi\left(\mathbf{PGH}^T\right)\right\|_F^2 \quad \text{subject to} \quad 0 \le \mathbf{G}_{ik}, \mathbf{H}_{jk} \le 1,\ \forall i,j,k$$

where function φ converts image from CIE XYZ space to CIE Lab space. In fact, the squared Frobenius norm divided by the total pixel number N corresponds to the color difference metric ΔE_{76}. In our implementation, we optimize the objective function with more sophisticated color metric ΔE_{94} since the most updated CIEDE2000 is too discontinuous to optimize. We solve this optimization problem via alternating direction method of multipliers(ADMM, [Boyd et al. 2011]), as

$$\begin{aligned}\underset{\{\mathbf{G},\mathbf{H}\}}{\text{minimize}} \quad & \left\|\beta\mathbf{I}^{(lab)} - \varphi(\mathbf{X})\right\|_F^2 \\ \text{subject to} \quad & \mathbf{X} - \mathbf{PGH}^T = 0 \\ & 0 \le \mathbf{G}_{ik}, \mathbf{H}_{jk} \le 1,\ \forall i,j,k\end{aligned}$$

where X is an intermediate value. Then, we can solve the problem by following a sequence of simple update rule

$$\begin{aligned}\mathbf{X} &\leftarrow \underset{\{\mathbf{X}\}}{\arg\min} \left\|\beta\mathbf{I}^{(lab)} - \varphi(\mathbf{X})\right\|_F^2 + \frac{\rho}{2}\left\|\mathbf{X} - \mathbf{PGH}^T + \mathbf{U}\right\|_F^2 \\ \{\mathbf{G},\mathbf{H}\} &\leftarrow \underset{\{\mathbf{G},\mathbf{H}\}}{\arg\min} \frac{\rho}{2}\left\|\mathbf{X} - \mathbf{PGH}^T + \mathbf{U}\right\|_F^2 \\ \mathbf{U} &\leftarrow \mathbf{U} + \mathbf{X} - \mathbf{PGH}^T\end{aligned}$$

where X is updated using Gauss-Newton method, and G,H are updated using NMF.

Projector Prototype

The prototype consists of a modified Texas Instruments LightCrafter 0.3 WVGA DLP chipset projector, Lumencor six LED fiber-coupled analog light engine, control electronics, and software.

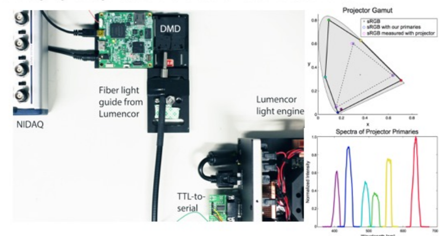

FIGURE 2: Projector Prototype

Implementation

PNMF is implemented in Matlab. The X-update step in ADMM is based on parallel per-pixel operations. We speed up this step considerably by implementing it as a mex module that loops through the pixels for each Newton iteration. We use the scaling factor $\beta = 1$ which never compromises image brightness. The ρ parameter in ADMM is chosen as 1.5E+06, which heuristically yielded consistent and fast convergence. For PNMF, we use 1,500 total ADMM iterations, where within each iteration there are 5 Newton iterations for the first update step, and 10 NMF iterations for the second step. For the comparisons to NMF, we use 35,000 NMF iterations, which was adequate to yield convergence to a delta between iterations smaller than at least 1e-6.

On an Intel i7-4790 3.6 GHz processor with 8 GB RAM, for 1,500 iterations on a 512×512 pixel image, PNMF took 9,500 seconds and for 35,000 iterations on the same image, NMF took 13,500 seconds.

Experiment Result